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AI and Automation in Railway Inspection and Maintenance

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Abstract

Artificial intelligence and automation are becoming central to railway inspection and maintenance, particularly for large networks such as China's railway system. The analysis links network-scale maintenance pressure, automated inspection platforms, non-destructive testing, smart sensing and data-driven decision support. Artificial intelligence creates value when defect recognition is connected to maintenance action rather than treated as an isolated classification task. Robots, on-vehicle systems, ground penetrating radar, ultrasonic inspection, smart sleepers and internet-of-things monitoring should operate within a closed inspection-to-maintenance loop. China provides a useful setting because its conventional and high-speed railway networks require inspection methods that are low-cost, repeatable and scalable. Representative technologies are organised by asset class, data type, interpretation task and maintenance output. Practical barriers include data quality, sensor calibration, limited labelled defects, cross-line generalisation, safety assurance and life-cycle cost justification. The framework supports a shift from isolated intelligent inspection tools to system-level railway maintenance automation.

Keywords: railway inspection, railway maintenance, artificial intelligence, railway automation, life-cycle cost, predictive maintenance.

1 Introduction

Railway infrastructure now has to reconcile network scale, operating speed and service reliability. In China, the operating railway network reached about 165,000 km by the end of 2025, including more than 50,000 km of high-speed railway [1]. This scale changes the maintenance problem. Inspection must cover conventional railways, high-speed railways, urban and regional lines, heavy-haul corridors and complex stations. High traffic density also leaves short possession windows for manual inspection and repair. These conditions create a strong operational need for inspection that is repeatable, high-throughput and evidence-based.

Traditional railway inspection still depends on skilled workers and specialised vehicles. Track recording vehicles and ultrasonic inspection vehicles provide essential measurements, but much of the inspection chain still relies on patrols, expert judgement and local experience. These tasks are dangerous, difficult, dirty and dull. They expose workers to traffic risk and harsh environments, while requiring attention to rare but consequential defects. Demographic pressure reinforces the problem. As the network grows and labour supply becomes more constrained, the sector must increase the productivity, consistency and traceability of each inspection action.

Artificial intelligence (AI) and automation offer one route to this transformation, but their railway value should be defined carefully. AI is often presented as a defect classifier that converts images or signals into labels. In maintenance practice, the more important question is how an inspection result changes a maintenance decision. A robotic fastener alarm, a ground-penetrating-radar fouling index, an ultrasonic flaw classification or a smart-sleeper warning becomes useful only when it is linked to location, severity, confidence, traffic exposure, maintenance cost and intervention constraints. Existing surveys show that machine learning in rail maintenance covers detection, prediction, diagnosis and decision support rather than classification alone [2]. Maintenance scheduling research similarly shows the need to fuse condition, planning and cost data [3].

Applications in China's railway system are a useful setting for examining this shift. The country combines large-scale modern infrastructure, intense operation and a strong engineering supply chain. The application landscape includes inspection robots, smart trolleys, on-vehicle measuring systems, ground penetrating radar (GPR), ultrasonic inspection, smart sleepers, micro-electromechanical system (MEMS) sensors and internet of things (IoT) platforms. Some technologies replace hazardous or repetitive inspection. Others add sensing channels that workers cannot provide at network scale, such as continuous vibration monitoring or repeated subsurface radar survey. The common direction is a shift from periodic visual inspection towards multi-source, data-rich and risk-based maintenance.

Using a framework-based synthesis, the analysis reviews AI and automation in railway inspection and maintenance. The scope is a review and application synthesis rather than a new experiment. Representative technologies and China-oriented application scenarios are organised into a closed loop that connects inspection need, automated sensing, data management, AI interpretation, maintenance decision-making and feedback learning. The framework maps the role of AI and automation across major railway asset classes, links the technology map to maintenance outputs such as work-order prioritisation, ballast cleaning, rail-defect verification and condition-based warnings, and identifies deployment barriers that must be addressed before intelligent inspection tools can become reliable maintenance infrastructure.

2 Framework-Based Synthesis

2.1 Scope and interpretation basis

The synthesis uses a framework-based approach rather than a systematic review protocol. Its purpose is to convert application material and relevant literature into a practical structure for railway inspection and maintenance. The starting point is the public-works problem faced by railways: a large network must be inspected frequently enough to maintain safety, comfort and availability, while inspection and maintenance costs remain acceptable over the asset life cycle. This life-cycle view is essential. An automated method that improves detection but creates excessive false alarms may increase workload. Conversely, a method with moderate classification accuracy may still be valuable if it stabilises trends, screens low-risk locations and directs scarce expert attention to critical assets.

The technical scope covers five application groups. The first is automated and robotic inspection of visible track components, including geometry, fasteners, sleepers, tunnel surfaces and clearance. The second is subsurface and ballast-bed inspection, especially GPR-based assessment of layer thickness, fouling, moisture and subgrade condition. The third is embedded or wayside monitoring with smart sleepers, MEMS sensors, temperature sensors and IoT devices. The fourth is rail internal-defect inspection using ultrasonic data and AI-assisted interpretation. The fifth is integration through smart trolleys and train-mounted systems that combine sensors and upload data to maintenance databases.

Commercial product names are kept in the background. The relevant issue is the engineering function of a robot or sensor, the data it generates and the maintenance decision it supports. Application examples from China indicate a move from laboratory prototypes to field tools, while also showing that real railway environments require robustness, affordability and maintainability. A low-cost device that can be deployed on many routes may have greater system value than a highly accurate device that remains isolated in a demonstration.

2.2 Closed-loop maintenance architecture

Figure 1 shows the proposed architecture. The loop starts from an inspection need, such as recurring fastener failure, suspected ballast fouling, abnormal vibration, rail-defect screening or continuous-welded-rail displacement. Automated sensing then converts asset condition into data through robots, trolleys, on-vehicle systems, GPR, ultrasonic inspection, cameras, accelerometers and temperature sensors. These data streams must be standardised, located, quality controlled and stored before AI interpretation becomes useful. The AI layer may include image classification, object detection, signal processing, anomaly detection, time-series prediction, data fusion and risk ranking. The maintenance layer then converts these outputs into inspection confirmation, repair scheduling, speed-restriction support, renewal prioritisation or long-term asset planning.

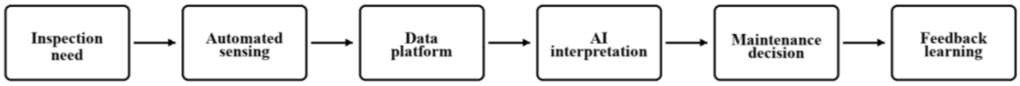

Figure 1: Framework for artificial intelligence and automation in railway inspection and maintenance.

The loop differs from a simple detect-and-report chain. In a mature maintenance system, interventions and later inspections should improve both models and maintenance rules. If an AI model flags fasteners as defective and maintenance staff confirm only a subset, that information should update the model and its decision threshold. If a GPR-based fouling index recommends ballast cleaning but post-cleaning track quality does not improve, the interpretation model or maintenance rule should be revised. If smart-sleeper alarms repeatedly coincide with thermal expansion and rail displacement, the same data stream can support seasonal management of continuous welded rail. Feedback is therefore a technical and organisational requirement, not an optional data-science feature.

3 Applications in China Railway Inspection and Maintenance

3.1 Robotic and on-vehicle inspection of visible track assets

Automated visual inspection is one of the most direct railway AI applications. Track components are repetitive, geometrically constrained and safety-critical, which makes them suitable for machine vision and robotic inspection. Deep-learning studies have shown the feasibility of track material segmentation and visual defect detection [4]. Recent reviews also show that railway inspection robots are moving from prototypes towards field applications [5].

In China, inspection robots and smart trolleys are being used or tested for track geometry, rail surface wear, fastener condition, tunnel defects, clearance checking and foreign-object detection. Figure 2 illustrates representative field platforms used in railway inspection contexts.

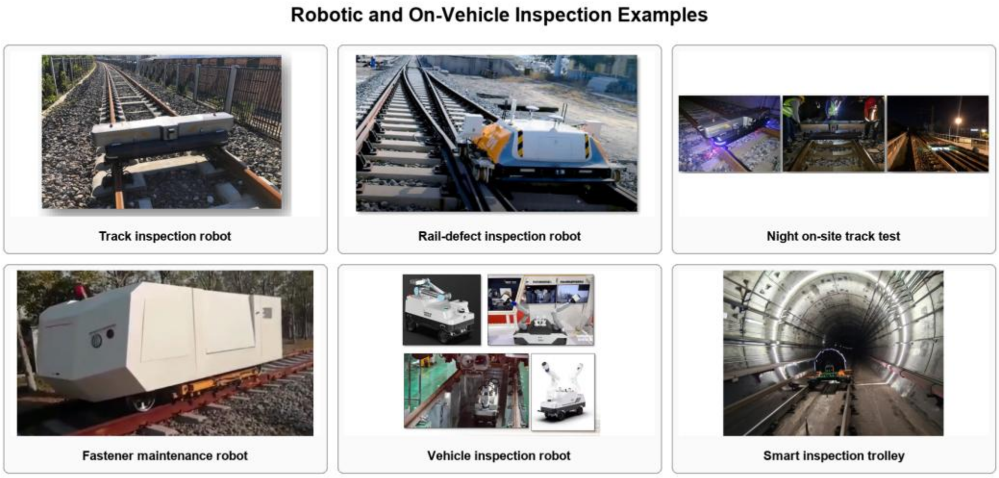

Figure 2: Representative robotic and on-vehicle inspection examples [5].

Robotic systems can also support task-level maintenance, including fastening, lubrication, ballast sweeping, grinding and measuring. Their value depends on reducing worker exposure, improving repeatability and fitting within short possession windows.

3.2 Ground penetrating radar for ballast and substructure assessment

GPR is a central non-destructive testing method for ballast and substructure inspection. It can support continuous assessment of layer thickness, layer boundaries, fouling, moisture, soft subgrade conditions and underground objects. However, antenna frequency, survey configuration and dielectric contrast strongly affect interpretation quality [6,7].

AI in GPR inspection should not be limited to classifying traces as normal or abnormal. It can identify stable features across radar traces, locate layer interfaces, detect local anomalies and combine radar evidence with track geometry or maintenance history. These models remain useful only if they preserve physical traceability.

China provides a strong test environment for GPR because large survey mileage can be accumulated across climates, ballast states and railway types. The key challenge is to build a calibrated interpretation chain that translates radar evidence into cleaning, drainage or verification decisions.

3.3 Smart sleepers, MEMS sensors and internet of things monitoring

Smart sleepers and distributed sensors shift railway inspection from periodic observation to continuous state awareness. Relevant concepts include self-sensing concrete, acceleration and strain measurement, energy harvesting, temperature monitoring and IoT communication [8].

The maintenance value of smart sleepers depends on feature design and deployment strategy. AI becomes useful when vibration, strain, force or temperature data can be linked to hanging sleepers, support loss, stiffness change, excessive vibration, displacement or abnormal thermal behaviour.

Continuous welded rail provides a clear example. Temperature and longitudinal displacement are safety-sensitive variables. AI can help learn seasonal behaviour, detect abnormal deviations and rank sites for field verification.

3.4 AI-aided ultrasonic rail defect interpretation

Internal rail defects remain a high-consequence inspection target. Ultrasonic vehicles and handheld systems generate B-scan or imaging data whose interpretation is labour-intensive and experience-dependent. Recent work shows that AI can support the classification of subtle rail-defect patterns from ultrasonic imaging data [9].

The practical value of ultrasonic AI lies in decision support: organising verification, reducing routine screening and standardising records. Because severe false negatives are unacceptable, deployment should use conservative confidence thresholds, expert review and clear rules for action or re-inspection.

In Chinese railway practice, AI-assisted ultrasonic interpretation can reduce repetitive work, support training and enable shared databases that link ultrasonic records, rail type, speed, traffic load, maintenance history and confirmed defects. Representative sensing and non-destructive testing examples are shown in Figure 3.

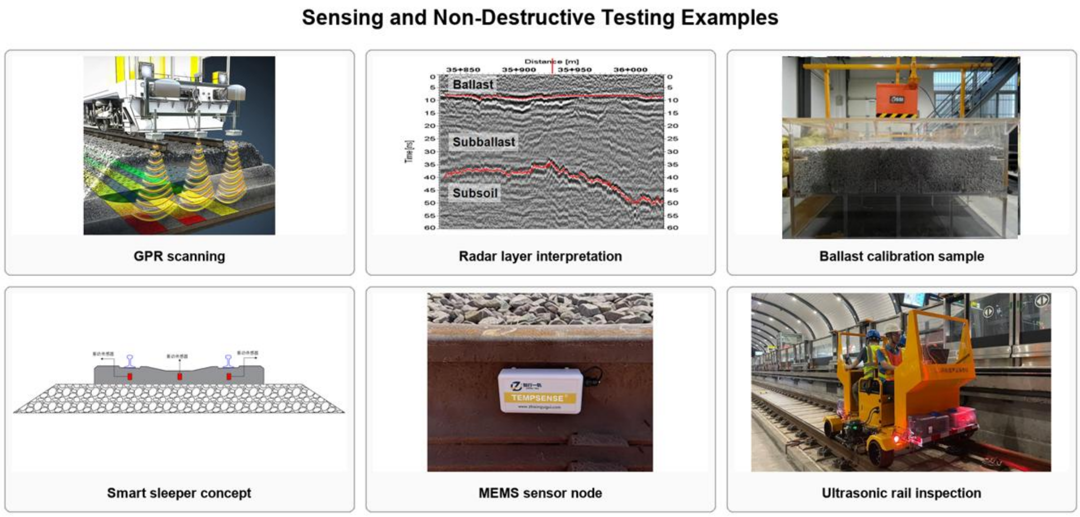

Figure 3: Representative sensing and non-destructive testing examples [6,8,9,10].

3.5 Integrated platforms and system-level deployment

A recurring lesson is that single-purpose tools must eventually be connected. Smart trolleys, train-mounted systems and depot platforms should link each defect candidate to location, asset identity, historical trend, maintenance intervention and cost.

Figure 4 maps the application logic for railway inspection in China. Network size creates scale pressure, while high traffic density and limited possession windows create maintenance pressure. Different sensors and AI tasks should therefore converge on a common maintenance platform. This direction is consistent with recent work on point-cloud, IoT and AI-supported railway infrastructure monitoring [11].

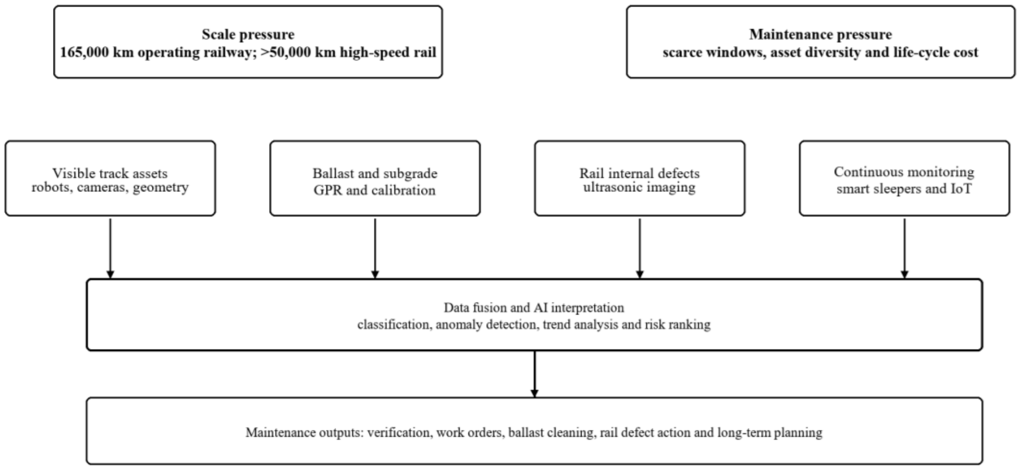

Figure 4: Application map for China railway inspection and maintenance.

4 Deployment Challenges and Discussion

The main barrier to AI-enabled railway inspection is the gap between controlled model performance and field reliability. Railway defects are rare, operating conditions change, sensors age and data distributions vary across lines. Tunnel images differ from outdoor images. GPR traces vary with moisture and ballast condition. Ultrasonic data depend on coupling and inspection speed, while smart-sleeper signals depend on train type, support condition and temperature. Large-scale deployment therefore requires data governance, field calibration, uncertainty reporting and confirmed feedback records. Each inspection record should include location, time, sensor settings, speed, environmental conditions and confirmation status where possible.

Many AI studies report accuracy, precision, recall or F1-score. Railway maintenance also needs value metrics: fewer missed hazards, lower worker exposure, fewer unnecessary interventions, shorter possession time and better maintenance planning. A fastener detector that cannot localise defects for repair crews has limited value. A GPR classifier that cannot distinguish urgent from non-urgent sites may create excessive work orders. Predictive maintenance is therefore the system-level result of reliable sensing, interpretable AI, maintenance feedback and cost-aware decision support.

Railway inspection is safety-critical, so AI should initially assist certified inspection responsibility rather than replace it. Human reviewers need access to the original image, signal or time series, the model output, the confidence score and the historical asset context. Maintenance rules should specify which outputs require immediate action, which require verification and which are used only for trend monitoring. This conservative organisation can support acceptance because AI reduces routine screening burden while leaving ambiguous and high-risk decisions to experts.

5 Conclusions and Contributions

The synthesis connects inspection need, automated sensing, data management, AI interpretation, maintenance decision-making and feedback learning in a single railway inspection and maintenance framework. Its value lies in treating AI as part of an inspection-to-maintenance loop rather than as an isolated classifier.

The synthesis shows that robots, smart trolleys and on-vehicle systems improve repeatability for visible assets. GPR provides subsurface evidence for ballast and subgrade assessment. Smart sleepers, MEMS sensors and IoT nodes enable continuous monitoring, while ultrasonic AI supports more consistent interpretation of internal rail defects. Integrated platforms are needed to connect these tools to asset history and maintenance decisions.

For China, network scale creates both pressure and opportunity. Large survey mileage and diverse operating conditions can support AI development, but they also make generalisation, data governance and safety assurance difficult. The next stage should focus on standardised records, calibrated field sites, uncertainty-aware models, human-in-the-loop verification and maintenance feedback. This boundary is important: intelligent inspection becomes useful only when it improves maintenance decisions under real operating constraints.

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